

## COMPUTATIONALLY INTELLIGENT MODELLING AND CONTROL OF FLUIDIZED BED COMBUSTION PROCESS

by

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Original scientific paper:

UDC: 539.374/.377:519.62/.63

DOI: 10.2298/TSCI101205031Ć

*In this paper modelling and control approaches for fluidized bed combustion process have been considered, that are based on the use of computational intelligence. Proposed adaptive neuro-fuzzy-genetic modelling and intelligent control strategies provide for efficient combining of available expert knowledge with experimental data. Firstly, based on the qualitative information on the desulphurization process, models of the SO<sub>2</sub> emission in fluidized bed combustion have been developed, which provides for economical and efficient reduction of SO<sub>2</sub> in fluidized bed combustion by estimation of optimal process parameters and by design of intelligent control systems based on defined emission models. Also, efficient fuzzy non-linear fluidized bed combustion process modelling strategy by combining several linearized combustion models has been presented. Finally, fuzzy and conventional process control systems for fuel flow and primary air flow regulation based on developed models and optimized by genetic algorithms have also been developed. Obtained results indicate that computationally intelligent approach can be successfully applied for modelling and control of complex fluidized bed combustion process.*

Key words: *computational intelligence, fluidized bed combustion, fuzzy systems, neural networks, genetic algorithms*

### Introduction

In fluidized bed combustion (FBC), besides fuel combustion chamber contains a quantity of particles of inert material such as sand or ash. The combustion air entering from below lifts mixed material keeping it in constant movement and forming a turbulent bed, which behaves like a boiling fluid. This essential feature is the basis for many excellent properties of the FBC technology but it also makes the process highly complex [1-3]. To match the process complexity, several aspects of the application of powerful computational intelligence techniques for FBC process modelling and control have been considered in this paper.

Harmful flue gas emissions such as sulphur oxides, nitrogen oxides, and carbon monoxide are result of the complex burning phenomena and the construction features of the plants. In addition to the developments in the plant construction and flue gas cleaners, also the optimization of the process operating conditions is an important and cost-effective way to affect these emissions, especially since possibility to reduce emissions is one of the main

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features of FBC technology. But to be able to optimize the plant operation, models for the variables of the overall cost function are required. With that and other aims concerning control of FBC plant in mind [4-6], in this paper models for the SO<sub>2</sub> emissions based on the computational intelligence techniques are considered.

Also, in this study conventional control process models linearized around different operational points have been combined by means of hybrid fuzzy model, which extends the model usability for wide range of plant working regimes. Suggested fuzzy model, based on Takagi-Sugeno-Kang (TSK) fuzzy reasoning, makes smooth interpolation of several linear models and therefore overcomes their rigid limitations.

Finally, genetic optimization has been considered for obtaining usable conventional and fuzzy controllers for regulation of the main FBC plant operational loops. Conventional proportional-integral-derivate (PID) controller and alternative fuzzy proportional-derivate (PD) controller design approaches have been considered, where controller parameters were optimized by real coded genetic algorithms. Quick response and modest overshoot of a closed loop system is of vast importance having in mind energy efficiency, flue gas emission, and plant safety.

Computationally intelligent modelling and control approach [7-9] applied in this paper is based on fuzzy logic, neural networks, genetic algorithms, and fuzzy clustering methodologies. Hybrid approaches have been used, such as trainable neuro-fuzzy structure that combines the theory of artificial neural networks (ANN) and fuzzy systems and that can benefit from both qualitative and quantitative available information. Learning methods of ANN enable these systems to learn from given training data sets, and due to the massive parallelism of the ANN real-time processing of larger data sets and graceful degradation of performance in the case of damage are provided. The fuzzy set theory enables the neuro-fuzzy systems to deal with the ambiguous or ill-defined data effectively and to present the learned information in a more human understandable form.

Soft computing models and control systems considered in this paper present extensions of the results that the authors obtained [4-6, 10] in the field of neuro-fuzzy-genetic modelling and control of FBC process and flue gas emissions. Besides that, group of authors [3, 11, 12] developed fuzzy-relation models of flue gas emission, adaptive prototypes for online NO<sub>x</sub> emission identification and Wiener logical models of FBC process, as well as genealogical decision trees and distributed logical processors for multivariable control of FBC. Other authors [13, 14] considered binary coded genetic optimization and genetic learning automata for conventional and fuzzy control based on a neuro-fuzzy models of combustion process. In some papers [15, 16] robust FBC control with predictive model based on fuzzy model and piecewise quadratic Lyapunov functions that guarantees stability in every work regime is suggested. Some novel results [17] considering advanced control of FBC are based on human-simulated intelligent control that can overcome conventional control disadvantages.

Combining numerical and linguistic information into system is the key-strategy obtained by computationally intelligent approach, since complexity of the FBC process makes application of conventional modelling and advanced control strategies difficult [4, 10, 13].

## **Fluidized bed combustion, experimental data and methodology**

### ***Fluidized bed combustion***

Combustion air entering from below in fluidized bed combustion [1, 2] lifts particles such as sand or ash that are present in combustion chamber, forming a turbulent bed and keeping them in constant movement when the fuel is added to the bed. Released heat from the



During these experiments oil shale was used as fuel. Signals were measured with a frequency of 1 Hz, and the process was operated changing the values of parameters. A sample of obtained measurement data is shown in fig 2.

Concentration of SO<sub>2</sub> was directly measured and then recalculated as percent of SO<sub>2</sub> removal from flue gas, which was used as training data for model output.

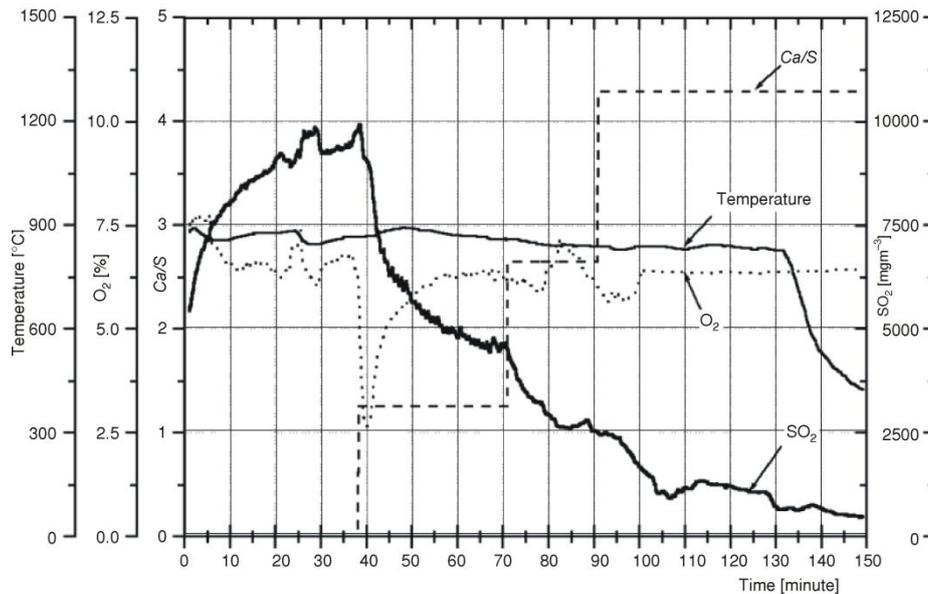


Figure 2. A set of experimental data used for training of neuro-fuzzy model

### **Computational intelligence techniques used for FBC modelling and control**

This section summarizes main computational intelligence techniques used for FBC modelling and control in this study, namely the basic architecture and the hybrid learning algorithm of adaptive neuro-fuzzy inference system (ANFIS) [9], modified mountain clustering (MMC) technique for initial neuro-fuzzy model structure determination [8, 24] as well as real-coded genetic algorithms [25].

#### *ANFIS structure*

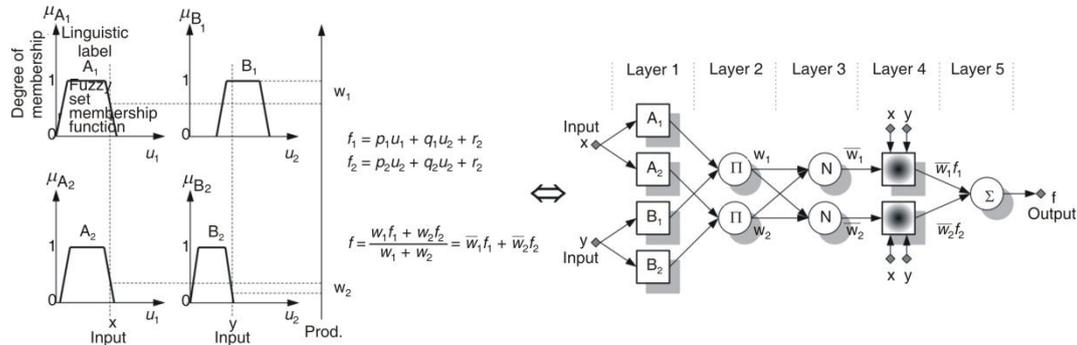
Consider a first-order TSK fuzzy inference system that consists of two rules:

- Rule 1: If  $X$  is  $A_1$  and  $Y$  is  $B_1$  then  $f_1 = p_1x + q_1y + r_1$ , and
- Rule 2: If  $X$  is  $A_2$  and  $Y$  is  $B_2$  then  $f_2 = p_2x + q_2y + r_2$ .

If  $f_1$  and  $f_2$  are constants instead of linear equations, we have a zero-order TSK fuzzy model. Figures 3(a) and (b) illustrate the fuzzy reasoning mechanism and the corresponding ANFIS architecture, respectively.

Node functions in the same layer of ANFIS are of the same function family. Note that  $O_i^j$  denotes the output of the  $i^{\text{th}}$  node in layer  $j$ .

*Layer 1:* Each node in this layer generates membership grades  $\mu$  of a linguistic label. For instance, the node function of  $i^{\text{th}}$  node might be:



**Figure 3. First-order TSK fuzzy model using trapezoidal membership functions and corresponding ANFIS architecture**

$$O_i^1 = \mu_{A_i}(x) = \max \left[ \min \left( \frac{x-a}{b-a}, 1, \frac{d-x}{d-c} \right), 0 \right] \quad (1)$$

where  $x$  (and also  $y$ ) is the input to node  $i$ ;  $A_i$  (and also  $B_i$ ) – the linguistic label (small, large, *etc.*) associated with this node, and  $a, b, c,$  and  $d$  – the parameter set that changes the shape of the trapezoidal membership function. Parameters in this layer are referred to as the premise parameters.

*Layer 2:* Each node in this layer, labeled with  $\Pi$ , calculates the firing strength of each rule via multiplication:

$$O_i^2 = w_i = \mu_{A_i}(x) \times \mu_{B_i}(y), \quad i=1, 2 \quad (2)$$

*Layer 3:* The  $i^{\text{th}}$  node of this layer, labelled with  $N$ , calculates the ratio of the  $i^{\text{th}}$  rule's firing strength to the sum of all rules firing strength:

$$O_i^3 = \bar{w}_i = \frac{w_i}{w_1 + w_2}, \quad i=1, 2 \quad (3)$$

*Layer 4:* Node  $i$  in this layer has the following node function:

$$O_i^4 = \bar{w}_i f_i = \bar{w}_i (p_i x + q_i y + r_i) \quad (4)$$

where  $\bar{w}_i$  is the output of layer 3 and  $p_i, q_i,$  and  $r_i$  is the parameter set. Parameters in this layer will be referred to as the consequent parameters.

*Layer 5:* The single node in this layer computes the overall output as the summation of all incoming signals overall output:

$$O_i^5 = \text{overall output} = \sum_i \bar{w}_i f_i = \frac{\sum w_i f_i}{\sum w_i} \quad (5)$$

#### The hybrid BP/RLSE learning algorithm

The hybrid learning algorithm of ANFIS consists of two alternating parts:

- (1) Back propagation/gradient descent (BP/GD) which calculates error signals (defined as the derivative of the squared error with respect to each node output) recursively from the output layer backward to the input nodes, and
- (2) the recursive least squares estimate (RLSE) method, which finds a feasible set of consequent parameters. We observe that, given fixed values of premise parameters, the overall output can be expressed as a linear combination of the consequent parameters:

$$f = \bar{w}_1 f_1 + \bar{w}_2 f_2 = (\bar{w}_1 x) p_1 + (\bar{w}_1 y) q_1 + (\bar{w}_1) r_1 + (\bar{w}_2 x) p_2 + (\bar{w}_2 y) q_2 + (\bar{w}_2) r_2 \quad (6)$$

Equation (6) can be recast as a matrix equation

$$\mathbf{A}\mathbf{X} = \mathbf{B} \quad (7)$$

where  $\mathbf{X}$  is an unknown vector whose elements are the consequent parameters. Least-squares estimate (LSE) of, namely  $\mathbf{X}^*$ , is sought to minimize the squared error  $\|\mathbf{A}\mathbf{X} - \mathbf{B}\|^2$ . Sequential formulas are employed to compute the LSE of  $\mathbf{X}$ . Specifically, let the  $i^{\text{th}}$  row vector of matrix  $\mathbf{A}$  defined in (7) be  $a_i^T$  and the  $i^{\text{th}}$  element of  $\mathbf{B}$  be  $b_i^T$ . Then

$$\mathbf{X}_{i+1} = \mathbf{X}_i + \mathbf{S}_{i+1} a_{i+1} (b_{i+1}^T - a_{i+1}^T \mathbf{X}_i), \quad \mathbf{S}_{i+1} = \bar{\mathbf{S}}_i - \frac{\mathbf{S}_i a_{i+1} a_{i+1}^T \mathbf{S}_i}{1 + a_{i+1}^T \mathbf{S}_i a_{i+1}}, \quad i = 0, 1, \dots, P-1 \quad (8)$$

where  $\mathbf{S}_i$  is often called the covariance matrix and the least-squares estimate  $\mathbf{X}^*$  is equal to  $\mathbf{X}_p$ . The conditions to initialize (8) are  $\mathbf{X}_0 = 0$  and  $\mathbf{S}_0 = \gamma \mathbf{I}$ , where  $\gamma$  is a positive large number and  $\mathbf{I}$  is the  $M \times M$  identity matrix, where  $M$  is the number of consequent parameters. For given fixed values of premise parameters, the estimated consequent parameters are known to be globally optimal.

### MMC clustering

The purpose of clustering is to distil natural groupings of data from a large data set, producing a concise representation of system behaviour. The quick subtractive or MMC clustering technique was developed by Yager/Filev and modified by Chiu [19]. The clustering of I/O data produces a set of cluster centers, and each cluster center acts as a prototypical data point that describes a characteristic mode of the system, and can be considered as the nucleus of a fuzzy if-then rule. In that way partitioning of the inputs and determination of the initial minimal fuzzy rule base can be performed.

Namely, if a collection of  $n$ -normalized data points  $\{x_1, x_2, \dots, x_n\}$  in an  $M$ -dimensional space is considered, measure of the potential of data point can be defined as:

$$P_i = \sum_{j=1}^n \exp(-\alpha \|x_i - x_j\|^2), \quad \alpha = \frac{4}{r_a^2} \quad (9)$$

The constant  $r_a$  is effectively the radius defining a neighbourhood. After the potential of every data point has been computed, the data point with the highest potential is selected as the first cluster center. If  $x_1^*$  is the first cluster center with potential  $P_1^*$ , the potential of each data point is revised by:

$$P_i \leftarrow P_i - P_i^* \exp(-\beta \|x_i - x_1^*\|^2), \quad \beta = \frac{4}{r_b^2} \quad (10)$$

where  $r_b$  is a positive constant larger than  $r_a$  in order to avoid high density of the cluster centers [19].

### Real coded genetic algorithm

The genetic algorithms (GA) are computational intelligence technique, inspired by Darwin's theory of biological evolution, that represent an alternative to the traditional optimal search approaches in which it is hard to find the global optimum for non-linear and multimodal optimization problems. GA maintains and manipulates a population of solutions and implements a survival of the fittest strategy in its search for better solutions. The fittest individuals of any population tend to reproduce and survive to the next generation thus improving successive generations.

Implementation of the GA requires the determination of six fundamental issues: chromosome representation, selection function, genetic operators, initialization, termination and evaluation function. Chromosome representation scheme determines how the problem is structured in the GA and also determines the genetic operators that are used. Each individual or chromosome is made up of a sequence of genes. Among various types of representations of an individual or chromosome, real-coded representation stands out for its efficiency and precision with more consistent results [25]. Also, real coding makes it possible to use large and even unknown domains for variables.

Selection of individuals plays a significant role in a GA since it determines which of the individuals will survive and move on to the next generation. A probabilistic selection is performed based upon the individual's fitness so that the superior individuals have better chances to be selected. There are several schemes for the selection process: roulette wheel selection and its extensions, scaling techniques, tournament, normal geometric, elitist models, and ranking methods.

The basic search mechanism of the GA is provided by the two types of operators: crossover and mutation, which are used to produce new solutions based on the existing solutions in the population. Crossover takes two individuals as parents and produces two new individuals while mutation alters one individual to produce a single new solution. An initial population is needed to start the GA procedure. The initial population can be randomly generated or can be taken from other methods.

The computational flowchart of the real coded genetic algorithm (RCGA) optimization process employed in this paper is shown in fig. 4. The GA moves from generation to generation until a stopping criterion is met. The

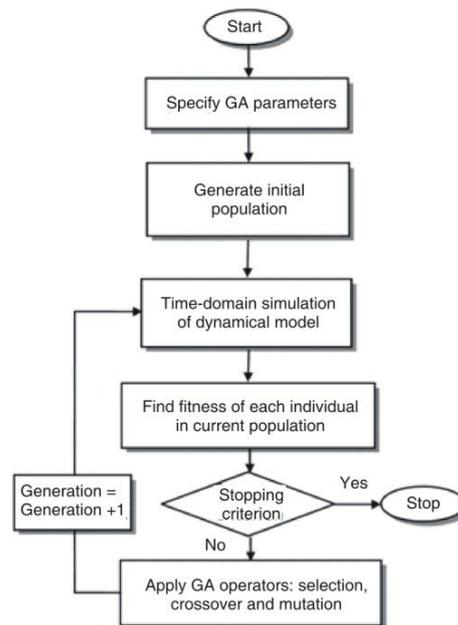


Figure 4. Flowchart of genetic algorithm

stopping criterion could be maximum number of generations, population convergence criteria, and lack of improvement in the best solution over a number of generations or target value for the objective function.

Evaluation functions or objective functions of many forms can be used in a GA so that the function can map the population into a partially ordered set.

## Computationally intelligent FBC modelling

### *Neuro-fuzzy desulphurization modelling*

Process operating conditions are an important and cost-effective way to affect FBC harmful flue gas emissions containing sulphur oxides. To be able to optimize the plant operation, neuro-fuzzy models have been considered for prediction of the SO<sub>2</sub> emissions based on the values of the most influential (changeable, *i. e.* adjustable) parameters.

Sulphur-dioxide removal from flue gas during the combustion process is possible by adding limestone in bed, which is considered to be one of the most important advantages of FBC. Harmful gaseous emissions are converted to solid material, which is eliminated from combustion bed, and there are also possibilities for its later usage. Degree of binding of sulphur is dependent on many parameters, where most important are: combustion temperature, molar ratio  $Ca/S$ , bed height, fluidization velocity, excess air ratio, primary/secondary air ratio, characteristics of limestone, size of particles of limestone, heating velocity of the limestone particle, *etc.* [1, 20, 21, 26].

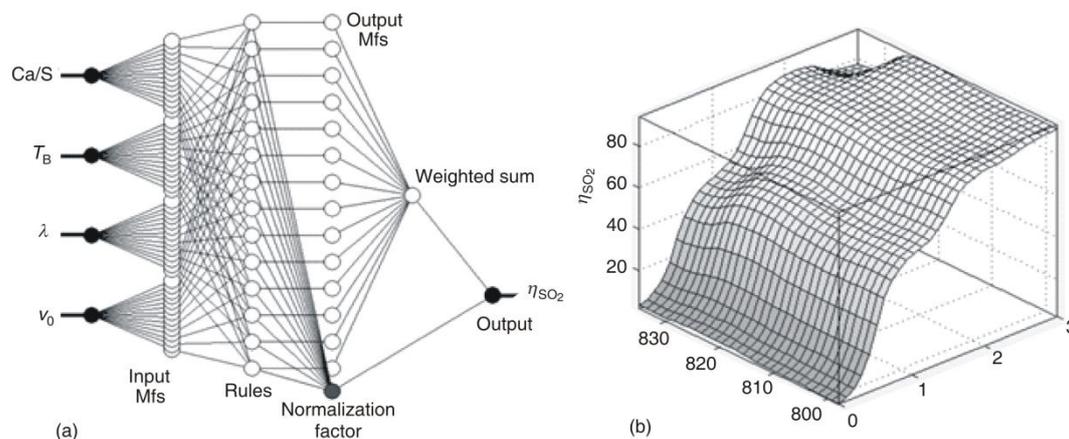
Input signals for SO<sub>2</sub> flue gas content model were selected based on *a priori* knowledge on the conditions affecting the formation and reduction of SO<sub>2</sub> in FBC process. Four model inputs selected were: molar ratio  $Ca/S$ , bed temperature TB, excess air ratio  $\lambda$ , and fluidization velocity  $v_0$ , while model output was percent of SO<sub>2</sub> removal from flue gas, denoted as  $\eta_{SO_2}$ . Ratio  $Ca/S$  is in practical operation of FBC experimentally near-optimally determined, and is selected as greater than one since desulphurization is improved when more limestone is added in bed than theoretically needed. Influence of bed temperature on flue gas SO<sub>2</sub> content is significant since below optimal temperature porosity of CaO is decreasing due to substantially smaller calcination of limestone, while on higher temperatures intense sintering occurs, closing pores and decreasing desulphurization. Excess air does not influence desulphurization process directly, but it has indirect positive effect. When fluidization velocity increases, time of contact of SO<sub>2</sub> and limestone particles decreases, so desulphurization is lowered. It was assumed that geometrical parameters of the fluidized bed plant cannot be changed, as well as fuel type or limestone quality and limestone particle size, so those influential parameters were not considered as possible model inputs.

To model FBC desulphurization, TSK fuzzy models [7] have been used having rule structure with fuzzy antecedent and functional consequent parts, which thereby qualify to be treated as mixed fuzzy and non-fuzzy models. TSK fuzzy models have the ability to represent both qualitative knowledge and quantitative information and allow for application of powerful learning techniques for model identification from data.

To develop models, the structure identification and parameter adjustment [8, 15, 24] tasks needed to be solved. The former determines I/O space partition, rule antecedent (*i. e.*, premise) and consequent variables, the number of IF-THEN rules, and the number and initial positions of membership functions. The latter identifies a feasible set of parameters under the given structure. For the problem of structure identification, a clustering technique presented in

previous section was used [5]. Exponential potential function was used to rank and select most representative cluster centers from plant I/O data, and these cluster centers are then used to generate an initial TSK fuzzy model. Also another approach was considered – partitioning based on expert process knowledge. Gaussian membership functions have been used. Model parameters adjustment was performed using efficient ANFIS neuro-fuzzy scheme [9] overviewed in previous sections. Using ANFIS initial TSK models obtained from the structure identification phase have been represented as generalized feed forward neural networks and trained with plant I/O data, thereby adjusting the parameters of the antecedent membership functions as well as those of the functional consequents with hybrid learning scheme.

Several versions of the ANFIS model structures were considered. First, versions with two ( $Ca/S$ ,  $T_B$ ) and four inputs ( $Ca/S$ ,  $T_B$ ,  $\lambda$ ,  $v_0$ ) were tested, while model output was  $\eta_{SO_2}$ . In all considered cases. One realized approach with four inputs is shown in fig. 5(a).



**Figure 5. (a) ANFIS network with 4 inputs and 14 rules and (b) output surface for trained fuzzy model with two input (Mfs – membership functions)**

Also, interpretability of the obtained results was issue of interest. Beside the fact that qualitative knowledge about the process was used along with available numerical data thanks to applied neuro-fuzzy modelling approach, obtained results after training can also be transformed into understandable information. For example in fig. 5(b) output surface for fuzzy model with two inputs and modest number of primary fuzzy sets with Gaussian membership functions, after training, is presented. It is obvious that some theoretical knowledge can be confirmed from such results, as the fact that there is optimal bed temperature which provides for maximal  $SO_2$  removal, after which further increase degrades  $SO_2$  removal process, and so on. Also, rules with trained optimal parameters can be arranged in readable form providing understandable conclusions that were extracted from data by the model [4].

Among several tests performed, one experimental verification of accuracy of model with four inputs and 14 rules from fig. 5(a) is presented in fig. 6, for 250 experimental data samples not used for model training. Possibility to perform multi-criteria optimization of the obtained models by application of genetic algorithms in order to achieve increased accuracy and/or interpretability of the models has been also tested. For this purpose presented GA with real coding have been used [5, 10].

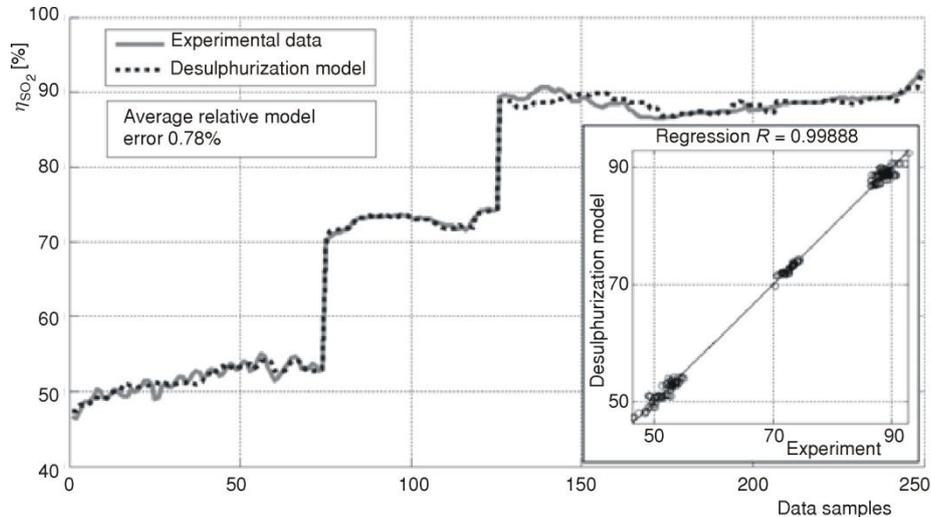


Figure 6. Experimental verification of accuracy of trained fuzzy model with four inputs

### Hybrid fuzzy FBC model

For development of the FBC plant main control loops, a basic combustion process model is required. Control oriented non-linear [27] and linear [11, 12] mathematical models of FBC process are based on mass and energy transfer. Combustion model inputs are fuel flow  $Q_c$  [ $\text{kg s}^{-1}$ ], primary air flow  $F_p$  and secondary air flow  $F_s$  [ $\text{Nm}^3 \text{s}^{-1}$ ]. Measurable system variables are bed temperature  $T_B$  [K], freeboard temperature  $T_F$  [K] and flue gas oxygen content  $C_F$  [%].

In this paper, a computational intelligence model based on fuzzy inference mechanism is proposed. The suggested fuzzy model intelligently interpolates linear models that are the result of the Lyapunov linearization around several characteristic operating points, in the form:

$$\frac{d\mathbf{x}^i(t)}{dt} = \mathbf{A}_i \mathbf{x}^i(t) + \mathbf{B}_i \mathbf{u}(t), \quad \mathbf{y}(t) = \mathbf{C}_i \mathbf{x}^i(t) \quad (11)$$

The idea was to overcome rigid limitations of the linear model, where the model is only valid near the operating point. By means of fuzzy model such limitations can be overcome and the fuzzy model can produce correct output for an arbitrary operating point. This approach allows the usage of linear models from [11, 12] and optimization of models explained in [4-6, 10].

Decisive fuzzy model inputs are measurable state variables, namely bed and freeboard temperatures  $T_B$  and  $T_F$  and flue gas oxygen content  $C_F$ , which define operating points of the linearized models. Other fuzzy model inputs are outputs of linear models  $y_i$ , value of combustion power  $P_{\text{comb}}$ , that are intelligently blended by the fuzzy model in order to generate overall model output  $y$ . Since the suggested fuzzy model is used as an interpolating supervisor of several differently linearized models, the TSK fuzzy reasoning was used [7], with linear dependencies in the consequential part of fuzzy rules, and free members equal to

zero. For realization with  $m$  submodels, linearized around  $m$  operating points and with outputs  $y^1, y^2, \dots, y^m$ , implemented  $k$ -th fuzzy rule is:

$$\text{Rule}_s^k: \text{if } \langle \text{operating point} \rangle^k \text{ then } \hat{y} = a_{k1}y^1 + a_{k2}y^2 + \dots + a_{km}y^m \quad (12)$$

All parameters  $a_{k1}, a_{k2}, \dots, a_{km}$  of the fuzzy rule are equal to zero, except for one which equals one. Every fuzzy rule defines one linear model for appropriate operating point identified in the antecedent rule part, selecting appropriate linear model for each characteristic operating point.

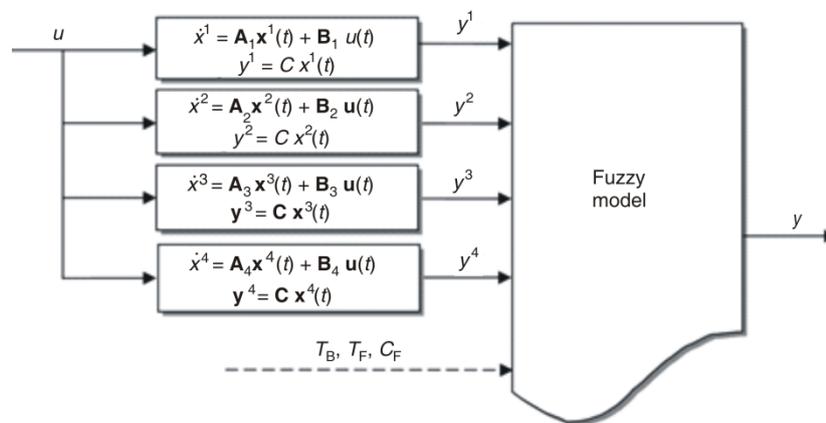


Figure 7. Fuzzy model

Model activates more than one fuzzy rule for different values of input but with diverse activation levels, so it is obvious that suggested realization makes smooth interpolation of singular linear models. Also, fuzzy model produces appropriate model output for the operating points that are not included in several optimally adjusted linear models. A scheme of fuzzy model based on non-linear model linearized around 4 characteristic operating points is shown in fig. 7.

### Intelligent FBC control

#### *Intelligent control of FBC desulphurization*

Computationally intelligent desulphurization models developed in previous section are intended to be used as approximators for determination of optimal process parameters in relation to flue gases  $\text{SO}_2$  removal. Models are to be integrated in FBC boiler's control system at supervisory level, and have the task of estimating parameters for basic control loops. Optimization of emissions demands compromises between different aims, and proposed models provide inputs for the optimization cost function which defines optimal balance between plant's thermal efficiency and emissions.

Beside described usage, following the ideas from [3, 6, 11, 28] developed models can be integrated in an expert system, which advises plant operators when limits for  $\text{NO}_x$ ,  $\text{SO}_2$ , and  $\text{CO}$  emissions are reached and helps to stabilize burning conditions. Such a system

provides easy access to the knowledge concerning emissions and helps operators to act quickly and efficiently, while effects of actions can be clearly seen. Such a system can be used not only in plant operation, but also for training. Its structure is shown in fig. 8.

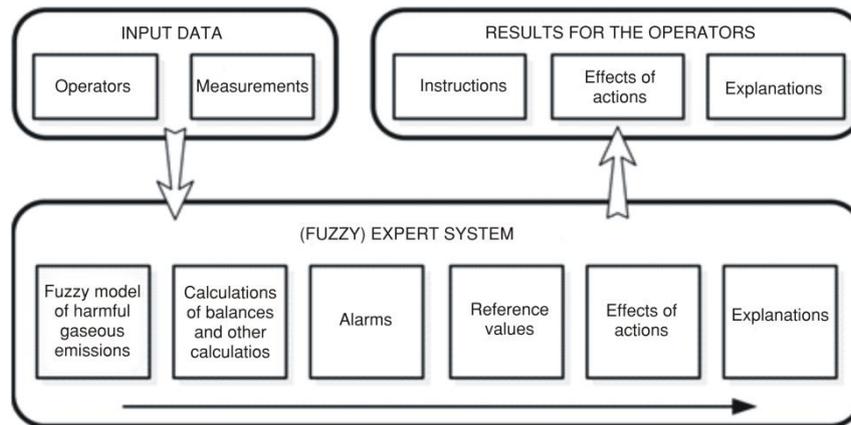


Figure 8. Expert system for monitoring emissions in FBC boiler plant

The main power of the proposed approach lies in centralized acquisition of all sources of information about the process, whether they origin from the operators' experience, theoretical knowledge about the process or measured data. Expert system can also potentially be based on computational intelligence, *i.e.* it can also be fuzzy.

Beside proposed static models of the emission of  $\text{SO}_2$  in boilers with FBC, identification of dynamic fuzzy models for the sake of application in the framework of adaptive control of FBC process has been considered as potentially feasible concept.

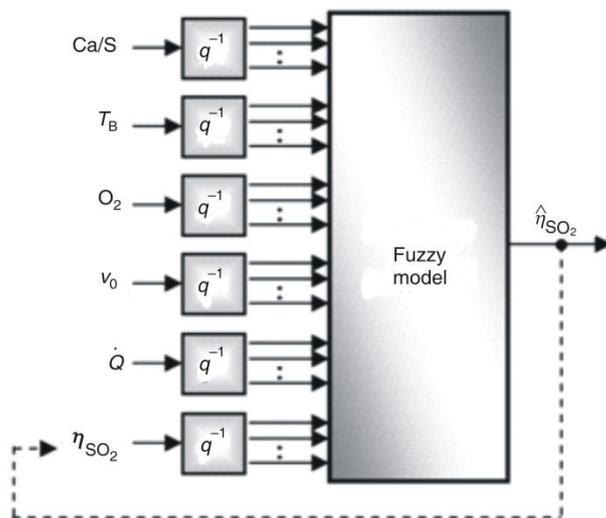


Figure 9. Dynamic fuzzy model of the  $\text{SO}_2$  emission with FBC

For dynamic modelling of the emission widely used strategy of external dynamics has been applied. This concept allows for the efficient application of fuzzy models that represent static approximators for modelling of dynamic systems, which has application in control systems as its final aim. Term “external dynamics” originates from the fact that non-linear dynamic model can be divided into two parts: non-linear static approximator and external bank of delay elements. Figure 9 shows the extension of the basic idea of static modelling to a dynamic version of a model.

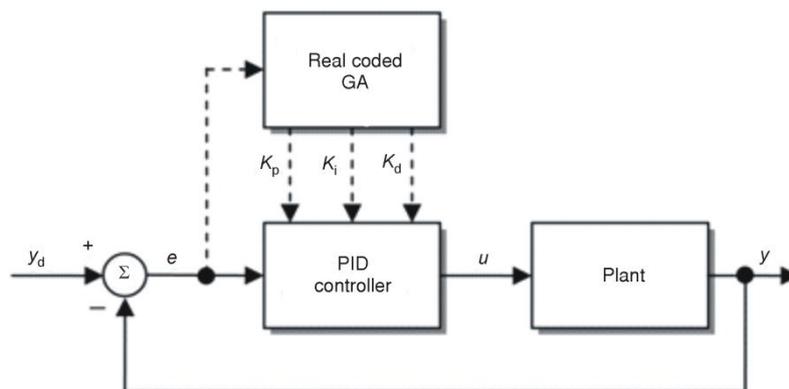
**GA optimized conventional and fuzzy control of FBC**

Efficiency of combustion process depends on the burning completeness and on the waste heat taken away in the flue gas by the excess air flow. The higher the burning rate and the smaller the waste heat, the higher the efficiency. However, excess air is required for ensuring complete combustion. The O<sub>2</sub> content of the flue gas is directly related to the amount of excess air. The aim of the combustion control, from the efficiency point of view, is to keep the O<sub>2</sub> content around 3-6% [3]. In multi-fuel fired FBC power plants, this is a difficult task due to the inhomogeneous properties of the fuel. In [13] the idea of usage of the binary coded genetic algorithm for the optimal FBC PD controller tuning is presented. To the contrary to that work, in this paper real coded genetic algorithms for optimal PID controller and fuzzy PD controller tuning were suggested, along with improved fitness functions and different plant model.

The combustion model used, based on the linear model developed in [11, 12] calculates combustion power ( $P_{comb}$ ) and flue gas components ( $C_F$ ) including the oxygen content, from the fuel flow, primary air flow  $F_p$ , and secondary airflow  $F_s$ . The oxygen and combustion power controller consists of two parallel PID controllers. The fuel flow controller is driven by the oxygen content error signal. The second PID controller regulates combustion power by changing primary airflow. The structure of the PID controller is:

$$\frac{U}{E}(s) = K_p + \frac{1}{s}K_i + sK_d \tag{13}$$

where modifiable parameters are PID controller proportional ( $K_p$ ), integral ( $K_i$ ), and derivative ( $K_d$ ) gains,  $U(s)$  and  $E(s)$  are Laplace transforms of control and error signals  $u(t)$  and  $e(t)$ , while  $s$  denotes Laplace's complex variable. System is linearized at operating point  $\bar{Q}_C = 2.6 \text{ kg/s}$ ,  $\bar{F}_P = 3.1 \text{ Nm}^3/\text{s}$ ,  $\bar{F}_S = 8.4 \text{ Nm}^3/\text{s}$ ,  $\bar{W}_C = 165 \text{ kg}$ ,  $\bar{C}_B = 0.042$ ,  $\bar{C}_F = 0.031$ ,  $\bar{T}_B = 749 \text{ }^\circ\text{C}$ ,  $\bar{T}_F = 650 \text{ }^\circ\text{C}$ , and  $\bar{P} = 21.1 \text{ MW}$ . The RCGA were used for tuning PID controller gains through genetic algorithms optimization variables set  $\Theta = [\theta_1, \theta_2, \theta_3, \theta_4, \theta_5, \theta_6] = [K_{p1}, K_{i1}, K_{d1}, K_{p2}, K_{i2}, K_{d2}]$ , as shown in fig. 10.



**Figure 10. RCGA for PID controller parameter optimization**

In the implemented algorithm a population of 60 individuals, an elitism of 2 individuals, initial range [0, 50] and a scattered crossover function were used. All the members were subjected to adaptive feasible mutation except for the elite. The individuals were randomly selected by the Roulette method. The fitness function used was sum of oxygen content relative error, combustion power relative error and relative value of maximum oxygen content overshoot (in order to additionally penalize overshoot and therefore try to suppress oscillatory behaviour):

$$f(\theta) = k_1 \sum_1^M \frac{|y_{O_2} - \hat{y}_{O_2}|}{\hat{y}_{O_2}} + k_2 \sum_1^M \frac{|y_P - \hat{y}_P|}{\hat{y}_P} + k_3 M \frac{|\max(y_{O_2})|}{\hat{y}_{O_2}} \quad (14)$$

where  $k_1$ ,  $k_2$ , and  $k_3$  are weight factors and  $M$  is the number of sampling data points. In our case  $k_1 = 2$ ,  $k_2 = 1$ , and  $k_3 = 1$ , emphasizing importance of oxygen content directly related to the flue gas emissions, combustion quality, and energy efficiency.

Stabilization of system with initial disturbances, where the flue gas oxygen content is 2.1%, and the initial plant power is 24 MW for 8 minutes controlled by PID controllers with RCGA tuned parameters is shown in fig. 11. PID parameters were obtained by careful alterations of the stated RCGA parameters. After several optimization runs, optimal parameters for two PID after 500 generations were  $K_{p1} = 83.20$ ,  $K_{i1} = 67.53$ ,  $K_{d1} = 87.45$ ,  $K_{p2} = 5.13$ ,  $K_{i2} = 0.1399$ ,  $K_{d2} = 17.24$  and the final optimal responses are shown in fig. 11 by full line.

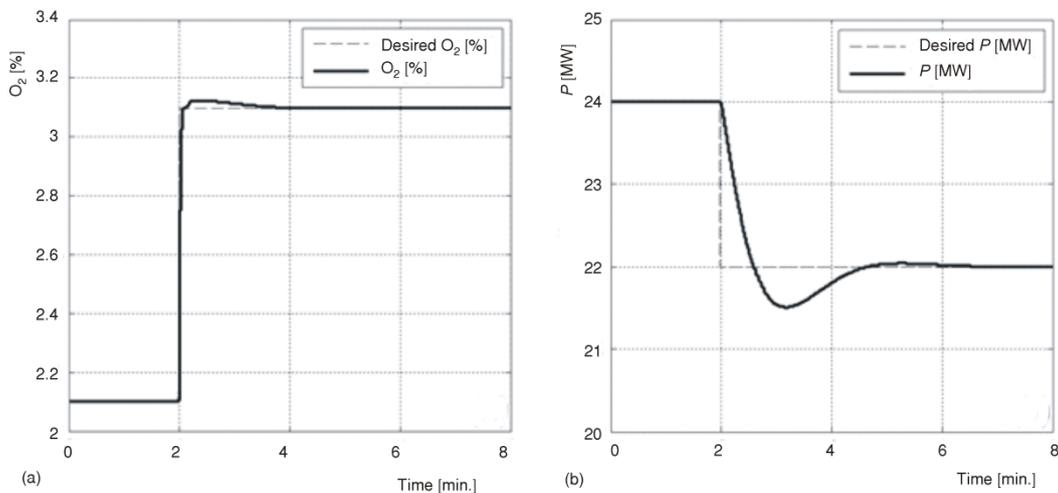


Figure 11. PID controllers (a) flue gas oxygen content and (b) combustion power stabilization

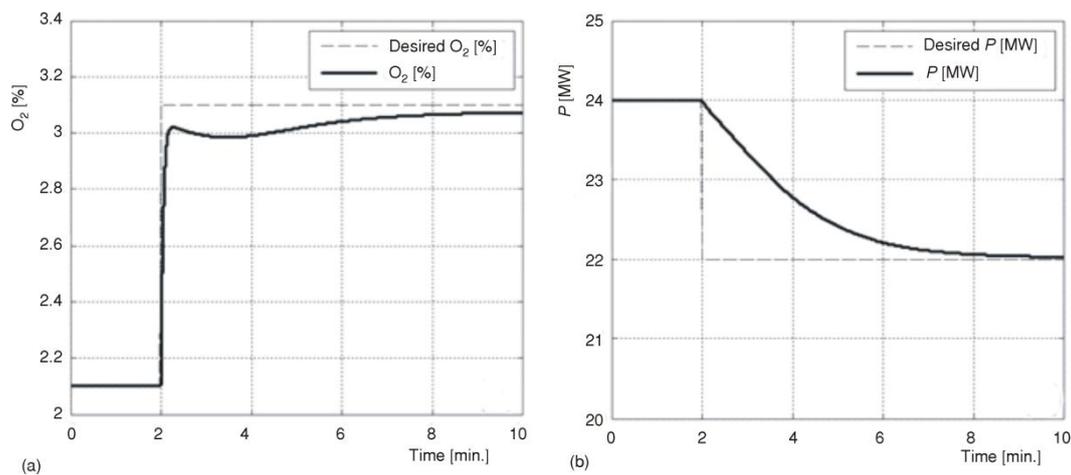
As an alternative to the conventional PID controller design approach, the fuzzy control [7, 8] for FBC control was also considered, namely two parallel fuzzy PD controllers for fuel and primary air were designed. The twin fuzzy PD controllers had the same inputs and tasks as with PID controllers. The error signal and error derivate for the controllers were normalized and divided in three regions each: low, medium, and high. The output membership functions of the controllers were singletons.

Optimal fuzzy controller normalization gain values  $K_{11}$ ,  $K_{12}$ ,  $K_{13}$ ,  $K_{21}$ ,  $K_{22}$ , and  $K_{23}$  (two for inputs and one for output per controller) were determined by RCGA. In the implemented algorithm a small population of 30 individuals, an elitism of 3 individuals, initial range [0, 50], a scattered crossover function, adaptive feasible mutation and Roulette selection were used. The fitness function was:

$$f(\theta) = \sum_1^M \frac{|y_{O_2} - \hat{y}_{O_2}|}{\hat{y}_{O_2}} + \sum_1^M \frac{|y_P - \hat{y}_P|}{\hat{y}_P} + M \frac{|\max(y_{O_2})|}{\hat{y}_{O_2}}, \quad (15)$$

where the first element minimizes the oxygen content relative error, second minimizes combustion power relative error and third element diminishes oxygen content overshoot. After 500 generations the following parameters were obtained:  $K_{11} = 15.5911$ ,  $K_{12} = 62.9364$ ,  $K_{13} = 39.8293$ ,  $K_{21} = 0.1029$ ,  $K_{22} = 0.5824$ ,  $K_{23} = 0.2214$ .

Stabilization of closed loop fuzzy controlled system with initial disturbances, where the initial flue gas oxygen content is 2.1%, desired oxygen content is 3.1%, the initial plant power is 24 MW and desired plant power is 22 MW for 10 minutes is shown in fig. 12.



**Figure 12. Fuzzy controllers (a) flue gas oxygen content and (b) combustion power stabilization**

Both PID and fuzzy controllers perform well, which indicates that RCGA optimization is useful tool in FBC controller tuning. Fuzzy control was tested as an alternative to conventional control as it opens possibility to relatively easily incorporate special actions regarding plant safety, energy efficiency, flue gas emission and others when certain circumstances occur in the system [4].

## Conclusions

Modelling and control problem that was studied in the paper originates from the fluidized bed combustion process, which is highly non-linear and complex thus making conventional modelling and control of FBC plants difficult.

Firstly, models for the flue gas  $SO_2$  content were identified using computational intelligence. Applied ANFIS networks were capable of capturing the non-linearities in

process data, the training was efficient and prediction accuracy of the obtained models was good. That goes along with other features, such as interpretability of the models, use of all sources of information on the process, *etc.*

Concisely recapitulated, triple usage of the developed computationally intelligent models of the emissions in FBC has been proposed for intelligent control of FBC boilers. That are, namely: application of static fuzzy models of emissions in order to provide for input values for optimization criteria, on the basis of which reference values for basic control loops are calculated; application of static fuzzy models in expert system that has the task of centralized treatment of information on harmful gaseous emissions and also to provide recommendations to plant operators; and application of dynamic fuzzy models of emission and their inverses for design of control in the framework of adaptive fuzzy control with internal model and fuzzy predictive control.

Proposed hybrid fuzzy FBC model based on the TSK fuzzy reasoning gives the optimal state of model output for the operating points that are not included in several optimally adjusted linear models that it uses. It makes smooth interpolation of linear models there fore overcoming their rigid limitations. The proposed fuzzy model represents an extension of the published results in a field of the FBC process modelling with control tasks in mind.

Stabilization of system with the initial disturbances controlled by PID controllers with optimally tuned gains as well as controlled by alternative fuzzy PD controllers with optimally adjusted parameters has also been presented. Real coded genetic algorithms were used for numerical calculation of optimal PID controller gains and fuzzy controller parameters. Both closed loop systems have rapid response and small overshoot. Such response is of vast importance having in mind energy efficiency, flue gas emissions and plant safety. A slower response increases chances for incomplete combustion that can lead to a major plant failure.

Based on the results reported in this paper, as well as on previous results published by the authors and others, it could be concluded that application of computational intelligence for modelling and control of fluidized bed combustion has both proven its potential and opened interesting directions for future research. Above all, combinations of neuro-fuzzy-genetic methodologies could be further explored to provide for more efficient integration of available expert knowledge about the process with other sources of information, such as measured data.

## Nomenclature

$Ca/S$	– molar ratio, [–]
$C_F$	– flue gas oxygen content, [–]
$F_p$	– primary air flow, [ $\text{Nm}^{-3}\text{s}^{-1}$ ]
$F_s$	– secondary air flow, [ $\text{Nm}^{-3}\text{s}^{-1}$ ]
$f_i$	– rule (linear equation output)
$O_i^j$	– node function
$P_{\text{comb}}$	– combustion power, [MW]
$Q_c$	– fuel flow, [ $\text{kg}\text{s}^{-1}$ ]
$T_B$	– bed temperature, [K]
$T_F$	– freeboard temperature, [K]
$u_i$	– system input
$v_0$	– fluidization velocity, [ $\text{m}^3\text{s}^{-1}$ ]
$w_i$	– rules firing strength
$y$	– system output

## Greek symbols

$\eta_{\text{SO}_2}$	– $\text{SO}_2$ removal from flue gas, [%]
$\lambda$	– excess air ratio, [–]

## Acronyms

ANN	– artificial neural network
ANFIS	– adaptive neuro-fuzzy inference system
BP/GD	– back propagation/gradient descent
FBC	– fluidized bed combustion
MMC	– modified mountain clustering
PD	– proportional derivative
PID	– proportional-integral-derivative
RLSE	– recursive least squares estimate

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